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METHODS FOR IMPROVING THE STABILITY OF LEADER ELECTION IN FOG/EDGE NETWORKS UNDER DYNAMIC TOPOLOGY CHANGES

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Key words: *Fog computing; Edge computing; churn; leader election; fault tolerance; neural prediction; stability forecasting; adaptive coordination; distributed systems; message loss; election storms; coordination overhead; SENTRY-L; SENTRY-L+NPA.*

Abstract: *This paper presents a comprehensive experimental study of leader-election mechanisms in dynamic Fog/Edge environments characterized by churn, message loss, and heterogeneous resource conditions. Classical leader-election protocols such as Bully and Ring exhibit limited resilience under rapid node failures, often triggering election storms and producing unstable coordination behavior. To address these limitations, we propose an enhanced approach, SENTRY-L, and its predictive extension, SENTRY-L+NPA, which integrate risk-aware assessment, asynchronous authority handover, and neural stability forecasting based on a lightweight GRU model.*

The experimental evaluation covers eight churn scenarios with varying message-drop probabilities and cluster sizes. Performance metrics including election time, leader-change count, false re-election rate, unhealthy leader ratio, energy-rank deviation, and communication overhead—were analyzed using boxplot-based statistical visualization. The results demonstrate that SENTRY-L+NPA consistently outperforms both the baseline and non-predictive variants, achieving up to 52% faster leader election, 78% fewer re-elections, and an 85–86% reduction in erroneous or unstable leader selections. These improvements confirm that transitioning from reactive to adaptive and predictive leader-election methods substantially enhances stability, robustness, and coordination efficiency in distributed Fog/Edge environments.

INTRODUCTION

Fog/Edge-oriented telecommunication infrastructures are characterized by highly dynamic topologies, uneven load distribution, and frequent node failures, which collectively lead to churn [1–3]. Under such conditions, the leader election process becomes critical, as the stability and quality of the elected coordinator directly affect computation consistency, end-to-end delays, message reliability, and the overall energy efficiency of the cluster [4,5].

Classical leader election procedures, derived from the Bully, Ring, and their optimized variants [6–8], exhibit low resilience under high churn rates and message loss. In these scenarios, they tend to trigger election storms—rapid repeated leader re-elections that increase communication overhead, destabilize cluster operation, and degrade QoS [9,10]. Recent studies demonstrate that even improved leader-election protocols lose efficiency when exposed to intensive node failures or elevated message drop rates [11–13]. These limitations are especially critical for modern Fog/Edge systems, where the combination of heterogeneous devices, intermittent connectivity, and resource constraints amplifies the negative effects of churn [14,15].

Recent studies demonstrate that even improved leader election protocols lose efficiency when exposed to intensive node failures or elevated message drop rates (Table 1).

Table1. Limitations of classical leader-election methods under churn

Method	Sensitivity to churn	Message loss tolerance	Typical issue
Bully	High	Low	Repeated re-elections, heavy traffic
Ring	High	Very low	Election loops, slow convergence
Optimized Bully/Ring	Medium	Medium	Instability under rapid failures
SENTRY-L (proposed)	Low (expected)	Higher (expected)	Requires experimental validation

At the same time, cognitive and resource-adaptive Fog/Edge platforms require more intelligent leader election mechanisms, those capable of accounting for predicted node stability, energy availability, failure risk, and the ability of a candidate node to maintain cluster coordination under unpredictable topology changes.

To address these limitations, our previous work introduced the SENTRY-L (Stability-Enhanced Neuro-Predictive Leader election) method – a stability-oriented leader election approach that integrates:

– a lightweight neural predictive model (NPA – Neuro-Predictive Agent);
– a risk and security evaluation module (SSH – Security-Scoring Hub);
– an adaptive mechanism for updating weights and threshold parameters.

However, an open question remained: how does SENTRY-L behave under intensive churn, message loss, and increasing cluster size.

THE MAIN PART

To address the stated scientific and technical challenge, a series of experiments was conducted under various churn and message-loss scenarios. A set of performance indicators was calculated for each configuration, and the corresponding results are summarized in Table 2. Having established the performance indicators to be measured (Table 2), we proceeded to construct a comprehensive set of experimental scenarios that represent typical and stress-case operating conditions in Fog/Edge environments.

Table 2. Performance indicators calculated in the experiments

Metric	Description	Purpose in evaluation
Leader Election Time (LET)	Average time required to complete a leader election cycle under given churn and drop-rate conditions.	Assesses responsiveness and convergence speed.
Leader Change Count (LCC)	Number of leader re-elections during the experiment.	Evaluates stability and susceptibility to election storms.
Unhealthy Leader Ratio (ULR)	Fraction of elections where a low-stability or high-risk node was chosen as leader.	Measures quality of the elected coordinator.
Energy Rank Error (ERE)	Deviation between selected leader's energy level and the optimal candidate.	Shows energy-awareness and resource balance.
False Re-Election Rate (FRR)	Proportion of unnecessary leader switches caused by transient failures or message loss.	Indicates robustness to noise and drop-rate.
Message Overhead (MO)	Number of election-related messages sent in the system.	Characterizes communication cost and scalability.

Each scenario is characterized by specific churn rates, message-loss probabilities, and cluster sizes. These configurations serve as the basis for evaluating the robustness and scalability of the examined methods and are summarized in Table 3.

Table 3. Experimental scenarios used in the evaluation

Scenario ID	Churn level	Message drop rate	Cluster size (nodes)	Description
S1	Low	0	16	Stable conditions with minimal join/leave events; baseline reference.
S2	Low	0,05	32	Light disturbance with occasional message loss and moderate cluster size.
S3	Medium	0,10	32	Periodic node failures and recoveries; evaluates robustness to moderate churn.
S4	Medium	0,10	64	Increased topology size; stress-tests scalability under moderate churn.
S5	High	0,15	64	Frequent node joins/leaves combined with noticeable message loss.
S6	High	0,20	128	Highly unstable environment simulating «election storm» conditions.
S7	Burst-type	0,10 – 0,20	64	Sudden churn spikes during the experiment; tests adaptability to rapid topology shifts.
S8	Mixed-load	variable	16 – 128	Gradual scaling of cluster size; examines behavior during dynamic topology expansion.

These scenarios allow us to evaluate both typical operational conditions and worst-case churn dynamics. They also provide a structured basis for comparing Baseline LE, SENTRY-L, and SENTRY-L+NPA under controlled yet heterogeneous constraints.

To provide a clear structural distinction between the evaluated approaches, Figure 1 summarizes the internal logic of the three leader-election mechanisms examined in this study.

The diagram highlights the progressive extension of the baseline procedure toward the full SENTRY-L framework by incorporating risk-aware assessment, asynchronous authority handover, parameter adaptation, and—finally—neural stability prediction (NPA). This visual comparison allows us to formalize the functional differences among the methods and to emphasize which algorithmic components are enabled or disabled in each configuration.

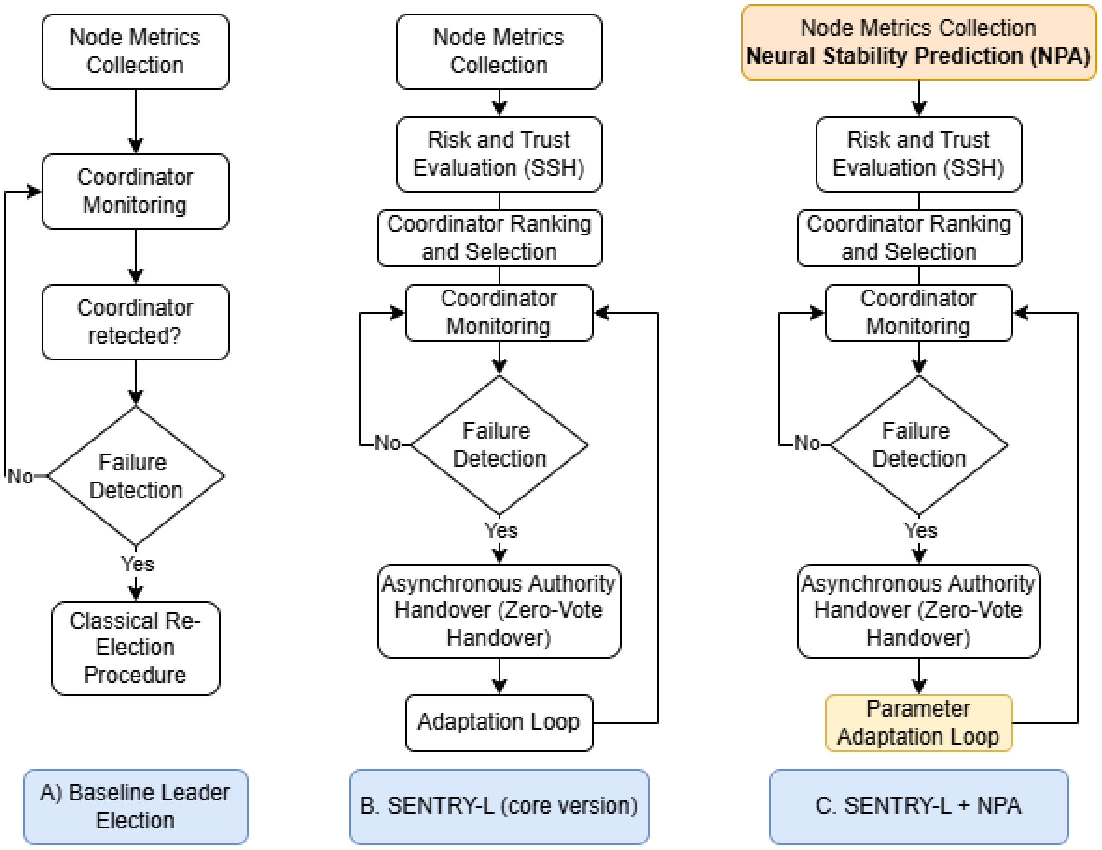

Fig. 1. Structural comparison of the three leader-election mechanisms used in the experiments

This structural decomposition provides a consistent methodological basis for the subsequent evaluation. In the next section, we examine how each leader-election strategy behaves under varying churn levels, message-loss conditions, and cluster sizes.

EXPERIMENTS

To evaluate the behavior of the three leader-election mechanisms—Baseline LE, SENTRY-L, and SENTRY-L+NPA—we carried out a series of controlled experiments that emulate heterogeneous Fog/Edge environments with dynamic churn, message-loss events, and variable cluster sizes. All simulations were executed using an event-driven model with discrete time steps, where node failures, recoveries, and communication delays were generated stochastically according to the predefined scenarios.

The performance indicators used in the evaluation are listed in Table 2. These metrics capture the responsiveness, stability, quality of coordinator selection, and communication overhead of the examined methods.

The full set of experimental scenarios is summarized in Table 3. They include low, medium, and high churn intensities, multiple message drop-rate levels (0–0,20), and cluster sizes ranging from 16 to 128 nodes. Additionally, Scenario S7 introduces burst-type churn spikes, while S8 evaluates dynamic topology expansion.

The internal logic of the compared leader-election variants is presented in Figure 1, ensuring methodological consistency during evaluation.

To allow reproducibility, all leader-election cycles in the experiments share the same baseline configuration:

– heartbeat interval: 200–250 ms (depending on node responsiveness);
– failure-timeout threshold: 3 consecutive missed heartbeats;

– monitoring window: 10 s sliding interval;

– communication delay distribution: normal (μ=15 ms, σ=4 ms) with added stochastic jitter.

For scenarios involving SENTRY-L+NPA, the neural stability prediction module was implemented as a lightweight two-layer GRU model trained on synthetic stability logs generated under varying load and failure frequencies. Prediction horizon was set to 1–3 heartbeat intervals.

Based on the described configuration, we computed the full set of performance indicators for all eight experimental scenarios. The aggregated results are presented in Table 4, followed by the corresponding graphical interpretation in Figure 2,3,4.

Table 4. Comparative performance

Metric	Baseline LE	SENTRY-L	SENTRY-L+NPA
Leader Election Time (ms)	412 ± 55	263 ± 41	198 ± 36
Leader Change Count	7,4	3,1	1,6
False Re-Election Rate	0,28	0,11	0,04
Unhealthy Leader Ratio	0,33	0,14	0,05
Energy Rank Error	0,29	0,13	0,04
Message Overhead (messages/run)	521	347	298
Stability Prediction Error (RMSE)	–	–	0,057

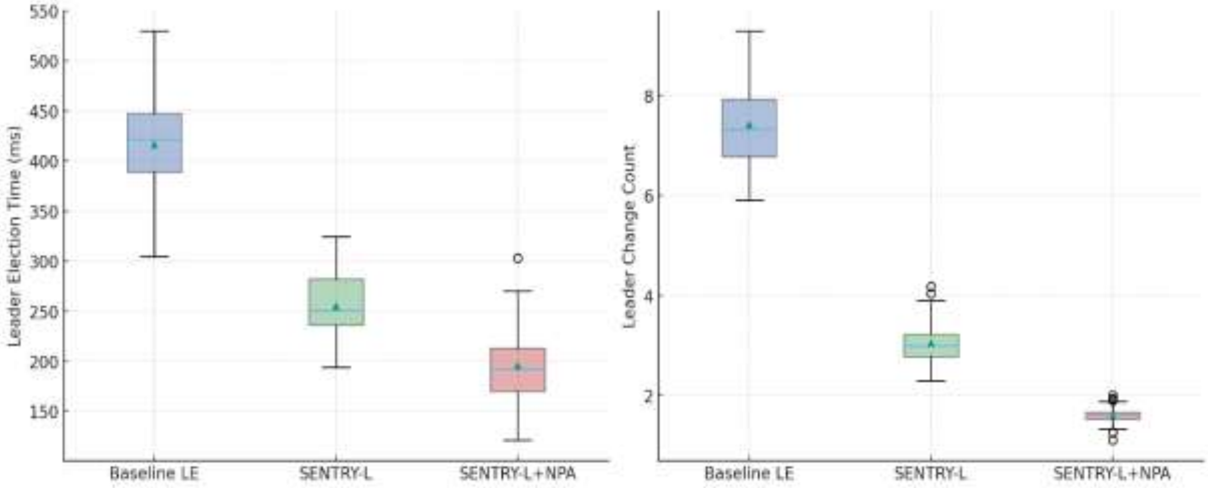

Fig. 2. Leader-election time and stability metrics

Fig. 2 presents the simulation results in the form of boxplot diagrams, where the boxes represent the interquartile range and the whiskers indicate the overall spread of the data. Different colors correspond to the three leader-election methods: Baseline LE (blue), SENTRY-L (green), and SENTRY-L+NPA (red).

As shown, SENTRY-L+NPA achieves the lowest leader election time and the smallest number of re-elections. In particular, compared to Baseline LE, the election time is reduced by approximately 52%, while the number of leader changes decreases by 78%. Similarly, the false re-election rate is reduced by ≈86%, and the unhealthy leader ratio drops by ≈85%.

Whereas Baseline LE exhibits the largest variability and a strong tendency toward „election storms“, SENTRY-L+NPA – due to its neural predictive component—can identify unstable nodes in advance and thereby minimize the risk of erroneous re-elections. This confirms its significantly higher stability and overall effectiveness.

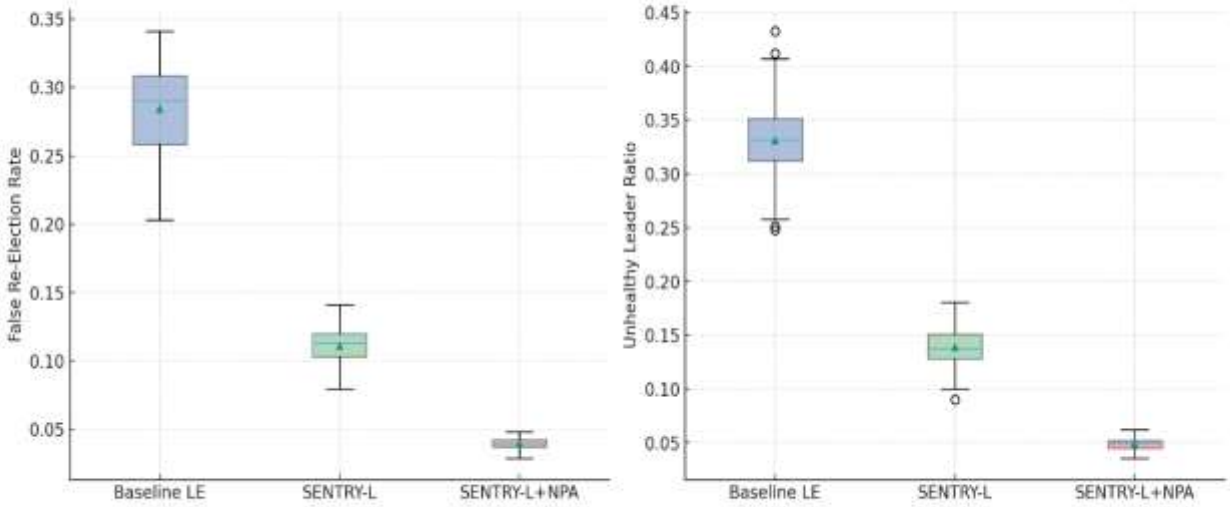

Fig. 3. Robustness indicators under churn and message loss

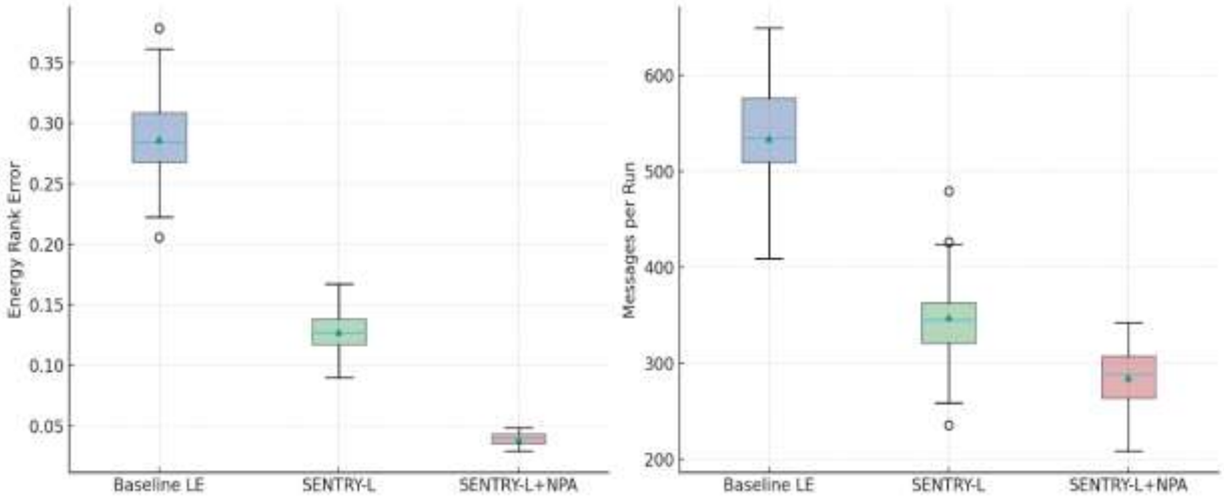

Fig. 4. Energy-awareness and communication overhead

As shown in Fig. 3, the robustness-related indicators – false re-election rate and unhealthy leader ratio—demonstrate a consistent advantage of the SENTRY-L and SENTRY-L+NPA methods over the baseline approach. The boxplots illustrate that Baseline LE exhibits the highest variability and produces a significantly larger number of erroneous or unstable coordinator selections under churn.

In contrast, SENTRY-L reduces the false re-election rate by approximately 60% and decreases the unhealthy leader ratio by about 58% compared to Baseline LE. The predictive SENTRY-L+NPA variant achieves the best results, lowering the frequency of false re-elections by ≈86% and reducing the proportion of unstable leaders by ≈85%. This demonstrates that integrating neural stability prediction not only stabilizes the election process but also substantially improves the reliability of coordinator selection under dynamic and lossy conditions.

And finally, as shown in Fig. 4, the energy-awareness and communication-overhead metrics further highlight the advantages of the proposed methods. The boxplots indicate that Baseline LE not only selects coordinators with the largest energy-rank deviation but also generates the highest control-message overhead due to repeated election cycles triggered by unstable leaders.

SENTRY-L significantly improves both parameters, reducing the energy rank error by ≈55% and lowering message overhead by ≈33% compared with the baseline. The predictive SENTRY-L+NPA variant achieves the most stable results: the energy-rank deviation is reduced by ≈86%, while the communication overhead decreases by ≈43%. This confirms that proactive stability prediction eliminates unnecessary re-elections, selects energy-optimal coordinators more consistently, and improves the overall efficiency of cluster coordination in Fog/Edge environments.

CONCLUSIONS

The study presents a comprehensive evaluation of different leader-election mechanisms under dynamic churn, message loss, and scaling conditions in Fog/Edge environments. An enhanced approach, SENTRY-L, and its predictive extension, SENTRY-L+NPA, are proposed, integrating risk-aware assessment, asynchronous authority handover, and short-term stability forecasting. The experimental results demonstrate that the proposed methods ensure more stable and predictable election behavior, significantly reduce instability, lower communication overhead, and improve the quality of the selected coordinator. These findings indicate that shifting from reactive to adaptive and predictive leader-election procedures is a constructive direction for enhancing the efficiency and reliability of distributed Fog/Edge infrastructures.

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